Dynamics of Orientation Selectivity in the Primary Visual Cortex and the Importance of Cortical Inhibition

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To test theories of orientation selectivity in primary visual cortex (V1), we have done experiments to measure the dynamics of orientation tuning of single neurons in the V1 cortex of macaque monkeys. Based on our dynamics results, we propose that a V1 cell’s orientation selectivity is generated mainly by both tuned enhancement and global suppression. Enhancement near the preferred orientation is probably caused by feed-forward input from LGN (plus amplification by cortical-cortical interaction). Global suppression could be supplied by cortical inhibition. Additionally, in about 1/3 of V1 neurons (usually the most sharply tuned) there is tuned suppression, centered near the cell’s preferred orientation but broader than tuned enhancement. These mechanisms also can explain important features of steady-state selectivity in the V1 neuron population. Furthermore, similar neuronal mechanisms may be used generally throughout the cerebral cortex.

Introduction
It has been thought from the time of its discovery that orientation tuning, as an emergent property in visual cortex, must be an important clue to how the cortex works and why it is built the way it is. There is a transformation in behavior from neurons in the LGN that are not tuned for orientation to orientation-tuned cells in V1 cortex (for example, in cat area 17, Hubel and Wiesel, 1962; in monkey V1, Hubel and Wiesel, 1968; Schiller et al., 1976; DeVlois et al., 1982). The visual stimuli that excite V1 can be well controlled, and the thalamic inputs to V1 from the lateral geniculate nucleus (LGN) have been measured with precision. Much has been learned about basic principles of cortical neurophysiology on account of the intense investigation of the transformation between LGN and V1. In this review, we present our own recent findings about the dynamics of orientation selectivity and a re-examination of steady-state selectivity, and then discuss what these new results imply about cerebral cortical function. All of our results point to the important role of intracortical interactions, especially cortico-cortical inhibition, in producing highly selective neurons in the cortex.

The motivation and rationale for our experiments came from considering different models or theories for visual cortical function, so it makes sense to begin our review there. There are two poles of thought about theoretical solutions for the problem of orientation selectivity: feedforward filtering, on the one hand, and attractor states where networks develop “bumps of activity” in the orientation domain as a response to weakly oriented input, on the other. Our own view, based on our experimental work and also on recent theoretical work and modeling by McLaughlin and Shelley and their collaborators (McLaughlin et al., 2000; Shelley et al., 2002; Shelley and McLaughlin, 2002), is somewhere in the middle; perhaps a good label for this view of the cause of orientation selectivity in V1 would be recurrent network filtering. What this means is that we think that feedforward excitation provides the orientation preference of V1 neurons, but that cortico-cortical inhibitory interactions within the V1 network are needed to make some V1 neurons highly selective for orientation.

Feedforward Models of Orientation Selectivity
The first model offered chronologically, and the first discussed here, is the feedforward model that is descended from the pioneering work of Hubel and Wiesel (1962). The HW model has the great virtue of being explicit and calculable. It involves the addition of signals from LGN cells that are aligned in a row along the long axis of the receptive field of the orientation-selective neuron. For example, in the often-encountered edge-sensitive orientation-tuned cells, Hubel and Wiesel postulated that a row of ON cells from the LGN would provide excitatory input in response to increments of illumination, and an adjacent parallel row of OFF cells would provide excitation for the opposite sign of contrast. There is some support for this kind of neural architecture in the ferret visual cortex (Chapman et al., 1991) and from dual recordings in LGN and cortex in the cat (Reid and Alonso, 1995). The experiment on cooling of cat V1 by Ferster et al. (1996) is an important result that was interpreted to mean that there is substantial orientation tuning of the collective thalamic input to a cortical neuron, consistent with the HW model. Chung and Ferster (1996) reached similar conclusions based on experiments with electrical stimulation. In spite of all this evidence, there is general agreement that the HW model predicts rather little orientation selectivity and therefore does not account for the visual properties of those V1 cells that are highly selective (Ferster, 1988; Sompolinsky and Shapley, 1997; Troyer et al., 1998; McLaughlin et al., 2000).

The reason for the shortfall of orientation selectivity in the HW model has been discussed before, but it is worth reviewing here. LGN cells have a low spontaneous rate but are quite responsive to visual stimuli. An LGN cell’s firing rate during visual stimulation by an optimal grating pattern has a sharp peak at one temporal phase and dips to zero spikes/s at the opposite temporal phase. Such nonlinear behavior depends on stimulus contrast: at very low stimulus contrast, the LGN cells’ minimum firing rate may not go down as low as zero
spikes/s. But at most stimulus contrasts used in experiments on cortex (that is, contrast > 0.1), the LGN cells' firing rate will hit zero on the downswing. This clipping of the spike rate at zero spikes/s makes the LGN cells act like nonlinear excitatory subunits as inputs to their cortical targets (Palmer and Davis, 1981; Tolhurst and Dean, 1990; Shapley, 1994). Since the HW model simply adds up the LGN sources, its summation of the clipped LGN inputs may cause it to have a nonzero response at 90° from the optimal orientation. In fact, depending on choice of neuronal spike threshold, the HW model can predict that the total number of spikes elicited by a drifting grating stimulus (or a bar stimulus) is the same at 90° as at 0°, though the spikes would be more spread out in time at 90° (Sompolinsky and Shapley, 1997; Troyer et al., 1998). Computational simulations of feedforward models with estimates of LGN convergent input derived from the work of Reid and Alonso (1995) support this analysis (Sompolinsky and Shapley, 1997; McLaughlin et al., 2000). An example is given in Figure 1, which shows a computation of the summed excitatory synaptic input from an HW model onto a cortical cell (cf. Sompolinsky and Shapley, 1997). Such a model produces a substantial LGN input to a cortical cell at 90° from the preferred orientation, as seen in the figure. But many cortical cells respond little or not at all at 90° from peak orientation. Therefore, feedforward convergence can be only a part of the story of cortical orientation selectivity.

It might be supposed that one could rescue the feedforward model by setting the threshold just high enough that the off-peak LGN input would be subthreshold (Carandini and Ferster, 2000). However, this maneuver will only succeed at one contrast. Figure 1 illustrates this; if one adds a threshold that makes the 10% contrast curve highly selective, the 50% contrast curve will have a very broadly tuned response. This has been pointed out several times before (cf. Ben-Yishai et al., 1995; Sompolinsky and Shapley, 1997; Troyer et al., 1998).

Such analysis of the HW model raises the following question: how does V1 reduce the large responses at orientations far from the preferred orientation, like those produced by feedforward LGN input illustrated in Figure 1? The present review is directed at answering this question.

The theoretical analysis above casts doubt on any experiments that aim to show how feedforward input completely explains orientation selectivity. Specifically, it is worth scrutinizing the experiments of Ferster et al. (1996) that were taken to be support for a feedforward model of orientation selectivity. The cooling experiments of Ferster et al. (1996) measured the amplitude of the first harmonic component (F1) in the intracellular voltage response to a drifting grating from a neuron in a cooled cortex. They cooled the cortex because they hoped to block all cortico-cortical synaptic transmission, and they measured intracellularly to pick up the synaptic potentials evoked, by hypothesis, only from LGN cells. Ferster et al. (1996) found the F1 responses of V1 cells in the cooled cortex to be as tuned for orientation as in the warm cortex. But this does not account for the orientation selectivity of the mean spike rate, which in the normal (warm) cortex is as selective as the F1 component of the spike rate. As we described above, the mean input current from the LGN to cortical cells is very weakly tuned for orientation. Therefore, the feedforward contribution to mean spike rate ought also to be weakly tuned. The F1 and mean have different tuning functions in the feedforward model because of the LGN spike threshold and the resulting clipping of the spike rate (see above).

What remains for theory and experiment to explain is how the cortical network produces the neurons in V1 that have a mean firing rate highly selective for orientation.

Models with Cortical Inhibition and Excitation

There is a well-known addendum to the HW model that would increase the orientation selectivity greatly. One can obtain increased orientation selectivity by adding inhibition that is more broadly tuned for orientation than excitation: either push-pull inhibition (Palmer and Davis, 1981; Tolhurst and Dean, 1990; Ferster, 1988, 1992; Troyer et al., 1998) or some other kind of cross-orientation inhibition (Bonds, 1989; Somers et al., 1995; Ben-Yishai et al., 1995; McLaughlin et al., 2000). Thalamocortical synapses are thought to be purely excitatory (Freund et al., 1989; Callaway, 1998), so the inhibition must come through cortical interneurons rather than directly from the thalamic afferents. Experiments on intracortical inhibition in V1 have given mixed results. Initially, Sillito's (1975) experiments with bicuculline suggested that intracortical inhibition is necessary for orientation tuning. However, the interpretation of these results is moot because of possible ceiling effects. Subsequent experiments of Nelson et al. (1994) blocking inhibition intracellularly have been interpreted to mean that inhibition onto a single neuron is not necessary for that neuron to be orientation tuned. On the other hand, an important role for intracortical inhibition has been indicated by more recent pharmacological experiments (Allison et al., 1995; Sato et al., 1996; Crook et al., 1998).

There are several models that explain cortical orienta-
tunet selectivity in terms of broadly tuned inhibition and more narrowly tuned excitation. One such theory of orientation tuning in cat cortex (Troyer et al., 1998) explains orientation selectivity in V1 in terms of push-pull inhibition (Palmer and Davis, 1981; Ferster, 1988, 1992; Tolhurst and Dean, 1990). Troyer et al. (1998) emphasize that the inhibition in their model is phase sensitive (push-pull), but in our view the phase sensitivity is irrelevant for the sharpening of orientation tuning. The main mechanism for sharpening of orientation tuning in the Troyer et al. (1998) model is cortico-cortical inhibition that is broadly tuned for orientation. In the Troyer et al. model, there is broadly tuned LGN convergent excitation as in the HW model, and then more broadly tuned inhibition that cancels out the wide angle responses but leaves the tuning curve around the peak orientation relatively unchanged. In having broadly tuned inhibition and more narrowly tuned excitation, this particular model resembles many other cortico-cortical interaction models for orientation selectivity (Somers et al. 1995; Ben-Yishai et al. 1995; McLaughlin et al. 2000).

More recently, McLaughlin and Shelley and colleagues (McLaughlin et al., 2000; Wieliaard et al., 2001; Shelley et al., 2002) attempted to design a realistic network model for macaque V1. They constructed a large-scale model (16,000 neurons) of four hypercolumns in layer 4c of macaque V1, incorporating known facts about the physiology and anatomy. This model accounts for many visual properties of V1 neurons, among them orientation selectivity. One novelty in this model is that the spatial strength of connections between neurons is taken to be the spatial density of synaptic connections revealed by anatomical investigations of cortex (e.g., Lund, 1988; Callaway, 1998). This model causes significant sharpening of orientation selectivity of V1 neurons compared to their feedforward LGN input. The mechanism of sharpening of orientation tuning is, as in the Troyer et al. (1998) model, broadly tuned inhibition. The big difference between this model and that of Troyer et al. (1998) is that in the McLaughlin et al. model the inhibitory conductance input to a cell is phase insensitive (and not push-pull). This is a consequence of the realistic simulation of cortical anatomy: inhibition onto a model cell is a sum from many inhibitory neurons, and each cortical inhibitory cell has a fixed phase preference that is different from that of other inhibitory neurons. This view of the nonselective nature of local cortico-cortical inhibitory interactions is supported by the measured phase insensitivity of synaptic inhibitory conductance in V1 neurons (Borg-Graham et al., 1998; Anderson et al., 2000; discussed in Wieliaard et al., 2001). Another distinguishing feature of the large-scale model of McLaughlin et al. (2000) is that it provides a mechanism for diversity in orientation selectivity; as discussed below, the observed diversity of orientation selectivity in V1 is striking.

Others have suggested that cortico-cortical excitatory interactions play a crucial role in orientation selectivity. Somers et al. (1995) presents an elaborate computational model for orientation tuning that includes both recurrent cortical excitation and inhibition as crucial elements. Douglas et al. (1995) argues for the importance of recurrent excitation in cortical circuits, reinforcing the message of Douglas and Martin (1991) on the “canonical microcircuit” of V1 cortex. A third paper in this genre is the work of Ben-Yishai et al. (1995). Ben-Yishai et al. offer an analytical model from which they make several qualitative and quantitative predictions. One of their theoretical results is that if recurrent feedback is strong enough one will observe a “marginal phase” state, in which V1 behaves like a set of attractors for orientation. The attractor states in recurrent excitatory models are discussed not only in Ben-Yishai et al. (1995) but also in Tsodyks et al. (1999). The concept is that the tuning of very weakly orientation-tuned feedforward signals can be massively sharpened by strong recurrent excitatory feedback. In such a network, the neurons will respond to any visual signal by relaxing into a state of activity governed by the pattern of cortico-cortical feedback. A similar idea was proposed in Adorjan et al. (1999).

Cortical Orientation Dynamics

In an attempt to provide data to test models of orientation selectivity, we used a reverse correlation method developed originally by Ringach et al. (1997a). The idea was to measure the time evolution of orientation selectivity extracellularly in single V1 neurons with a technique that drove most cortical neurons above threshold. The technique is illustrated in Figure 2. The input image sequence is a stimulus “movie” that runs for 15–30 min.
Grating patterns of orientations drawn randomly from a set of equally spaced orientations around the clock (usually in 10° steps) are presented for a fixed time (17 ms = 1 frame at a 60 Hz refresh rate in the early experiments reported in Ringach et al., 1997b, and 20 msec = 2 frames at 100 Hz refresh rate in the more recent experiments reported in Ringach et al., 2003). Each orientation is presented at 8 spatial phases, and the response is phase averaged. For each time offset, the probability distribution for orientation is calculated by incrementing the orientation bin corresponding to the orientation that precedes each of the N spikes and then dividing the bin counts by N. N is usually of the order of 5000 spikes. This is done for each time offset between spike and stimulus to create a sequence of orientation tuning curves, one for each time offset—an “orientation selectivity movie.”

In our earlier work with the reverse correlation technique (Ringach et al., 1997b), we reported that most cells in the input layers 4Cα and β have simple, “unimodal” dynamics and are relatively broadly tuned for orientation. By unimodal dynamics, we meant that after a time delay the response simply had a single peak in time and after the peak simply relaxed back to baseline. However, some cells in the output layers 2, 3, 4B, 5, and 6 showed “multimodal dynamics”: rebound responses, sharpening of the orientation tuning with time, and/or transient peaks of activity at off-optimal orientation. Also, in a few neurons in the output layers we observed a shift of the peak orientation with time. These resemble the “shifter” cells described by Shevelev et al. (1993). But shifter cells are the exception, not the rule, in macaque V1.

In more recent experiments on orientation dynamics (Ringach et al., 2003), we used a refined technique that revealed much more about the basic mechanisms of orientation selectivity. As shown in Figure 2, an additional pattern is added to the sequence: a blank stimulus at the mean luminance of the grating patterns. This allows us, for the first time, to measure global excitation and inhibition because, with this new technique, one can estimate whether the effect of one of the oriented patterns is greater or less than that of the blank pattern. If the probability of producing a spike by a pattern of orientation θ is greater than that of a blank, we view that as evidence that a pattern of orientation θ produces net excitation, while if the probability of producing a spike by a pattern of orientation θ is less than that of a blank, we take this as an indication of inhibition. Specifically, we take \( R(\theta, \tau) = \log[p(\theta, \tau)/p(\text{Blank}, \tau)] \). If the probability that angle θ evokes a spike is greater than that of a blank screen, then the sign of \( R \) is +. If the probability that angle θ evokes a spike is less than that of a blank screen, then the sign of \( R \) is −. If all angles evoke a response above what a blank does, then \( R(\theta) \) will have a positive value for all \( \theta \). A visual neuron equally well excited by stimuli of all orientation angles would produce a constant, positive \( R(\theta) \).

We can estimate several useful features of the tuning curve \( R(\theta, \tau) \), as shown in Figure 3. These include (1), the preferred orientation angle that elicits the biggest response, \( \theta_{\text{pref}} \), and its magnitude \( R_{\text{max}}(\theta_{\text{pref}}) \); (2), the orientation angle and magnitude of the minimum response, \( \theta_{\text{min}} \) and \( R_{\text{min}}(\theta_{\text{min}}) \); (3), the angle orthogonal to \( \theta_{\text{pref}} \), denoted \( \theta_{\text{ortho}} \), and its magnitude \( R_{\text{ortho}} \). The orientation modulation depth \( A(\theta) \) is a global measure of orientation selectivity because it is comparing the values of the tuning curve at two widely separated values of the angle \( \theta \). The bandwidth is a local measure of selectivity around the peak of the tuning curve.

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R(\theta, \tau) = R_{\text{max}} - R_{\text{min}}
\]

![Figure 3. Features of Orientation Tuning](image)

Features of the tuning curve \( R(\theta, \tau) \) include (1) the orientation angle of the peak response, \( \theta_{\text{pref}} \), and its magnitude \( R_{\text{max}}(\theta_{\text{pref}}) \); (2) the orientation angle and magnitude of the minimum response, \( \theta_{\text{min}} \) and \( R_{\text{min}}(\theta_{\text{min}}) \); (3) the angle orthogonal to \( \theta_{\text{pref}} \), denoted \( \theta_{\text{ortho}} \), and its magnitude \( R_{\text{ortho}} \); (4) the “modulation depth” of the tuning curve as a function of time \( \tau \), \( A(\tau) = R_{\text{max}}(\tau) - R_{\text{min}}(\tau) \); and (5) the dynamic half-bandwidth defined by half the width of the tuning curve at the “half-height,” which is equal to 1/2 \( [R(\theta_{\text{pref}}, \tau) - R(\theta_{\text{ortho}}, \tau)] \). \( A(\tau) \) is a global measure of orientation selectivity because it is comparing the values of the tuning curve at two widely separated values of the angle \( \theta \). The bandwidth is a local measure of selectivity around the peak of the tuning curve.

The shape of the orientation tuning curve \( R(\theta, \tau) \) changes with time, \( \tau \), and this dynamic behavior has a number of important properties that are revealed in Figure 4 for two representative V1 neurons. The black curves are graphs of \( R(\theta, \tau) \) at the time offset \( \tau_{\text{peak}} \) when the orientation modulation depth \( A(\tau) \) reaches its maximum value. The red and blue curves are graphs of \( R(\theta, \tau) \) at the two times bracketing \( \tau_{\text{peak}} \) at which \( A = 0.5* A_{\text{peak}} \); the red curve is at the development time \( \tau_{\text{dev}} \), the earlier of the two times when the modulation depth first rises from 0 to 0.5* \( A_{\text{peak}} \), and the blue curve is at the declining time \( \tau_{\text{decl}} \), when the response has declined back from \( A_{\text{peak}} \) to 0.5* \( A_{\text{peak}} \). One striking feature of these curves is that the dynamic tuning curve at the earlier time, \( R(\theta, \tau_{\text{dev}}) \), has a large positive pedestal of response, a sign of global excitation early in the response. This is just what one might predict from the analysis of feedforward models (see Figure 1), if indeed the earliest response measurable were predominantly feedforward excitation. But then, as the response evolves in time, the maximum value of \( R(\theta, \tau) \) at the preferred orientation grows only a little, while the responses at nonpreferred orientations...
neurons are depicted in Figure 5. The modulation depth, $A(\tau)$, normally increases to reach a peak and then declines back to baseline over a time course of 50 ms. An important feature is the positive sign of $R(\theta_{\text{min}}, \tau)$ and $R(\theta_{\text{ortho}}, \tau)$ early in the response, indicating that, on average, V1 cells tend to respond to all orientations early in the response. Another important feature of the data is the sharp downward change in time course of $R(\theta_{\text{min}}, \tau)$ and $R(\theta_{\text{ortho}}, \tau)$ before $A(\tau)$ reaches its peak value. Eventually, both $R(\theta_{\text{min}}, \tau)$ and $R(\theta_{\text{ortho}}, \tau)$ decline to negative values, meaning that later in the response orientations far from the preferred orientation are suppressive, not excitatory.

Another way to study the possible role of inhibition in selectivity is to measure the natural variation in selectivity and in suppression across the population of neurons and to calculate whether there is a correlation between them. In Figure 6, a global measure of selectivity, $A(\tau_{\text{peak}})$, is plotted against a measure of suppression, $R_{\text{min}}(\tau_{\text{dec}})$.
spike. In this study, we only analyzed the reverse correlations discussed just above. We divided the V1 population into groups based on empirical observation. While there is a wide variation in both modulation depth, \( A(\tau_{\text{sp}}, \omega) \), and in the measure of modulation, \( R_{\text{min}}(\tau_{\text{sp}}, \omega) \), there is a strikingly strong negative correlation between \( A(\tau_{\text{sp}}, \omega) \) and \( R_{\text{min}}(\tau_{\text{sp}}, \omega) \). This means that neurons that are highly selective (high values of \( A(\tau_{\text{sp}}, \omega) \)) tend to exhibit strong inhibition (more negative values of \( R_{\text{min}}(\tau_{\text{sp}}, \omega) \)).

The results about the population averages in Figure 5, and about the distribution of \( A_{\text{peak}} \) and \( R_{\text{min}} \) across the V1 population in Figure 6, support our hypothesis that there is a global mechanism of suppression that is rapid and that it contributes to the modulation depth of orientation selectivity at the peak time. This was also illustrated in the graphs of \( R(\theta, \tau) \) in Figure 4. These results could be explained with a theory in which feedforward excitation drives the early weakly-selective response, and then, with a very short delay, relatively rapid intracortical inhibition reduces the response at all orientations, acting like a global suppression. Additionally, in some macaque V1 neurons (like the one illustrated in Figure 4, lower panel) there is tuned suppression that enhances \( A(\tau) \) and also narrows the bandwidth of the response. Regression analysis reveals that this tuned suppression is found often in the most selective neurons (Ringach et al., 2003). Usually, there is both global and tuned suppression in the most highly selective neurons. However, at present the available realistic models of V1 predict only global suppression. A complete theory of V1 must account for both global and tuned suppression since both contribute to the time evolution of orientation selectivity. Recent evidence from intracellular recording in V1 indicates that a wide variety of patterns of cortico-cortical inhibition can influence orientation selectivity (Monier et al., 2003).

Suppression and Selectivity

In the experiments discussed in the preceding section, we did reverse correlation on a stimulus set of sine gratings with fixed spatial frequency but varying orientation, as in Ringach et al. (1997b). We also used another, related kind of experiment to study the role of off-peak suppression in orientation selectivity. In these experiments, we correlated cortical cells’ spike trains with a stimulus set consisting of sine gratings that varied in spatial frequency as well as orientation (Ringach et al., 2002a). Using a similar kind of reverse correlation procedure as in Ringach et al. (1997b), we calculated the probability of getting a spike from a particular spatial frequency, orientation > stimulus pair. Then we calculated a response using a formula that resembles the expression used before for the orientation dynamics experiments; thus, \( R(\omega_0, \theta, \tau) = \log[p(\omega_0, \theta, \tau)/p(\text{baseline}, \tau)] \), where \( \omega_0 \) is spatial frequency and \( \theta \) the orientation angle, and, as before, \( \tau \) is time delay between stimulus and spike. In this study, we only analyzed the reverse correlation at \( \tau_{\text{sp}} \) the time of maximal response. The (noisy, approximately zero) responses to high spatial frequencies above the cell’s resolution limit provided a baseline so we could observe activation and suppression. When \( R \) is positive, we infer that the \( \omega_0, \theta, \tau \) stimulus pair was excitatory. But if \( R \) is negative, the stimulus was suppressive. The method and a schematic representation of the results are represented in Figure 7. The response to stimulus pair, \( \omega_0, \theta, \tau_{\text{sp}} \), is a surface that is represented as a pseudo-color plot in which red coloring indicates excitation and blue stands for suppression. Responses near zero in this graph are colored green. There is a zone of excitation around the preferred orientation and spatial frequency and a surrounding zone of suppression around the excitatory region on the graph.

Natural variation of selectivity and suppression can be studied in these experiments. What is interesting about the results across the V1 population is that suppression is seen at off-peak orientations and also at lower-than-peak spatial frequencies (blue regions close to the origin in Figure 8B). The suppression that is observed in these experiments probably is caused by the same process as in the orientation dynamics experiments discussed just above. We divided the V1 population into a group that had a maximal suppression that exceeded a criterion of four times the standard deviation of the noise in the response and another group with less than that criterion amount of suppression. The group that received significant suppression we labeled as S, while the group with suppression below criterion we
suppressive components. Therefore, there must also be a strong (negative) correlation between whether a cell was in the S or \(\tilde{S}\) group and its orientation selectivity, as shown in Figure 8A (Ringach et al., 2002a). The global selectivity measure used here was circular variance (CV) (Mardia, 1972), another measure of the modulation depth of the entire orientation tuning curve.

Circular variance is \(1 - \{\text{relative modulation of } m(i)\}\) as a function of \(i\). The relative modulation is the ratio of the best fitting Fourier component of the orientation tuning curve (with period = 180') divided by the average response. For a flat tuning curve, \(CV = 1\). For a very highly tuned tuning curve, \(CV \rightarrow 0\). CV reflects wide-angle responses that the bandwidth does not. We showed in a previous paper that there is good empirical positive correlation between CV and another global measure of orientation selectivity, \(\frac{\text{R}(i_{\text{off-peak}})}{\text{R}(i_{\text{peak}})}\) (Ringach et al., 2002b). Therefore, there must also be a strong (negative) correlation between CV and \(A\), the modulation depth of the tuning curve defined above as \(\log(\frac{\text{R}(i_{\text{off-peak}})}{\text{R}(i_{\text{peak}})})\).

All the cells in the S group, the cells showing off-peak suppression, had low to moderate CV in the spatial frequency, orientation experiment. But the cells in the \(\tilde{S}\) group had high circular variance, meaning weak selectivity. Therefore, there is a strong association between the presence of suppression in the spatial frequency, orientation experiment and orientation selectivity. But there is a further correlation. The steady-state orientation tuning curve also was measured in these same neurons, with drifting gratings at the optimal spatial and temporal frequency, for a duration of 4 s at high contrast (the Rayleigh contrast was 0.8). One can also calculate the CV of the steady-state responses for cells in the two groups determined from their response characteristics from the dynamics experiments, the S and \(\tilde{S}\) groups. It is interesting that there is a similar correlation of dynamic suppression with the steady-state CV, illustrated in Figure 8B. Again, the neurons in the S group have much lower CV than the \(\tilde{S}\) cells, meaning that they are, as a group, more highly selective for steady-state stimuli as well as for the dynamical stimuli that were used to classify the neurons.

**Diversity of Orientation Selectivity for Steady-State Stimuli**

The results of dynamics experiments led us to re-examine steady-state orientation selectivity with the same global measures we used for the orientation dynamics. We found new evidence for the diversity of orientation selectivity and also further evidence for the importance of inhibition in causing high orientation selectivity.

**Bandwidth and Circular Variance**

There are different ways to measure orientation selectivity, and they can tell us about different aspects of orientation selectivity. A traditional method is to determine the half-bandwidth of the tuning curve around the peak of the tuning (e.g., Schiller et al., 1976; DeValois et al., 1982). This tells one the shape of the tuning curve near the peak. However, it is the global shape of the tuning curve at all orientations that differentiates between different theories of the cortex. In the analysis of a large population of steady-state orientation tuning curves, we used circular variance, the measure introduced above that is used in circular statistics (Mardia, 1972). CV is affected by wide-angle responses, unlike the bandwidth measure. Therefore, CV reveals aspects of orientation selectivity that were not seen before with bandwidth. Other investigators have also used global measures for selectivity that are related to CV. For instance, among others, Chapman and Stryker (1993), Sato et al. (1996), and Dragoi et al. (2000) use an orientation selectivity index (OSI) that is \(1 - CV\).

Figure 9 illustrates the wide diversity of orientation selectivity that is revealed with the circular variance measure. The upper panel shows the CV distribution across a population of V1 neurons (from steady-state experiments with drifting sine gratings at high contrast = 0.8). The range of CV is between 0 and 1 by definition. The cells’ data are distributed almost uniformly on the CV of the steady-state responses for cells in the same population. There is a spread of bandwidths, but it is difficult to appreciate from this graph how diverse the cells are from the bandwidth distribution. It is worth mentioning that the bandwidth data are similar to those reported in earlier studies by Schiller et al. (1976) and DeValois et al. (1982). Bandwidth and circular variance do not always go together. This is illustrated in Figure 10, where one sees examples of diverse orientation tuning curves from the V1 population. The neuron whose tuning curve is illustrated in Figure 10A is an example of a narrow-bandwidth neuron with low CV. The cell in Figure 10B also has a small bandwidth, but its CV is fairly high because it responds to all orientations. Note that in all the graphs of Figure 10 the dashed horizontal line is the spontaneous spike rate measured when the stimulus is a blank screen held at the mean luminance of the patterned stimuli. Thus, elevation of the spike rate above...
Figure 10. Diversity of Orientation Tuning Curves
Examples of individual tuning curves in macaque V1 neurons. The x axis represents stimulus orientation and its scale is the same for all graphs, from 0° to 180°, as indicated in the lower plots. The y axis is the response of the cell in spikes per second. The lower limit on the y scale is zero for all graphs, and the upper limit is indicated in each case. The dashed line represents the spontaneous rate of firing.

Figure 9. Circular Variance and Bandwidth Distributions
(A) Distribution of circular variance of steady-state tuning curves for 308 macaque V1 neurons. Circular variance is defined in the text.
(B) Distribution of half-bandwidth at 1/2-height for the same V1 population. The steady-state tuning curves were measured with drifting sine gratings optimized for size, spatial frequency, and temporal frequency, and for high contrast (Rayleigh contrast ∼ 0.8).

the dashed line means net excitation, while reduction of the response below the dashed line means that visual stimulation was net inhibitory. The neuron in Figure 10C exhibits such inhibition at orientations far from the preferred orientation and thereby has a much smaller CV than the companion neuron in Figure 10D, which has the same bandwidth but elevated responses at all orientations.

Inhibition in Steady-State Tuning Curves
The reduction of a steady-state response below spontaneous levels far from the preferred orientation is another marker of cortical inhibition in orientation selectivity. This phenomenon was noticed and illustrated originally by DeValois et al. (1982). However, the significance of this result was previously hard to appreciate because one did not know if this was an isolated or a common observation. Figure 11 from our recent study of steady-state orientation selectivity (Ringach et al., 2002b) indicates that suppression is common in steady-state orientation tuning curves. In this figure, the size of the points is an index of CV: the larger the point, the smaller the CV, as indicated in the right hand side of the figure. Thus, the larger points are for cells that are more orientation selective. The two axes of the plot are the spontaneous firing rate on the vertical axis and the spike rate at the orientation orthogonal to preferred on the horizontal axis. The dashed unity line is where cells would be plotted for which the orthogonal spike rate is the same as the spontaneous; such cells would receive no net suppression or excitation far from the preferred orientation. Cells plotted above and to the left of the dashed line are those cells for which orthogonal stimulation causes net suppression because the orthogonal spike
rate is less than the spontaneous. Cells that are plotted to the right and below the unity line are those that are excited by orthogonal stimulation above the spontaneous level. Note that many neurons lie to the left and above the dashed unity line, meaning that evidence for cortical inhibition in steady-state orientation tuning curves is quite prevalent in V1. Also, the most selective neurons also are the ones that receive suppression. The steady-state orientation tuning data are quite consistent with the results of the different dynamical experiments described above (Ringach et al., 2002a, 2003).

Discussion
The data in Figure 4 from the orientation dynamics experiment demonstrate that early excitation in V1 is very broadly tuned for orientation, just as predicted for models of feedforward convergence like the HW model (see Figure 1). Indeed, in simulations of the dynamics experiments with a large-scale network model of V1, McLaughlin et al. demonstrated that feedforward excitation generates dynamical orientation tuning curves with very high circular variance, meaning poor selectivity, at all time offsets between stimulus and spike (see Figure 2 in McLaughlin et al., 2000). Therefore, to us, an important question about orientation selectivity in V1 is, as we have stated it above, how does the cortex suppress the feedforward excitation far from the preferred orientation? What our assembled experimental results show is that inhibition in the cortex answers the question for those V1 neurons that are highly selective for orientation. The inhibitory signals must be fairly rapid, though not quite as fast as in arrival at the V1 neuron as the earliest excitatory signals. Also, inhibition appears to persist longer than excitation, as illustrated in Figure 5. Additional compelling evidence for the important role of inhibition in orientation selectivity has come from experiments on intracellular recording from neurons in cat V1 (Borg-Graham et al., 1998; Monier et al., 2003). Furthermore, the very elegant pharmacological experiments of Sato et al. (1996) showed directly that when cortical inhibition in macaque V1 was weakened by pharmacological blockers, neuronal orientation selectivity was reduced because the response to off-peak orientations grew stronger relative to the peak response (cf. especially Figure 8 in Sato et al., 1996). This is further support for the ideas that the feedforward excitatory input is very broadly tuned in orientation and cortical inhibition suppresses the responses far from the preferred orientation. The importance of cortical inhibition has been suggested also in models of the cortex (Troyer et al., 1998; McLaughlin et al., 2000; Wieland et al., 2001).

There is a possibility that tuned cortico-cortical excitation may contribute also to enhancement of orientation selectivity by boosting the response only around the preferred orientation, as suggested by the data in the lower panel of Figure 4. The possibility that in addition cortico-cortical excitation could enhance orientation selectivity was suggested previously in theories of V1 (Bendishai et al., 1995; Somers et al., 1995). It will be necessary in future work to analyze the dynamics of inhibition and excitation in cells from different cortical layers and in cells of different functional types to understand why the orientation dynamics of V1 neurons are so diverse.

In the Introduction we reviewed previous experiments that were taken to support a completely different point of view, namely that the pattern of feedforward thalamic input is enough to determine orientation selectivity. Our results as a whole are not consistent with this viewpoint. Recently, there have been two studies with dynamical stimuli that have been interpreted as supporting the feedforward theory. Gillespie et al. (2001), recording intracellularly in cat V1, reported that the bandwidth of orientation tuning curves did not change with time in their dynamic experiments. We believe that they did not observe the bandwidth changes that we documented in macaque V1 (Ringach et al., 2003) because their experiments did not have sufficient time resolution. However, Gillespie et al. (2001) do report a change in the intracellular baseline with time that reinforces our observations on the dynamic growth of inhibition. Therefore, our interpretation of the results of Gillespie et al. (2001) is that they support the concept that inhibition plays an important role in enhancing orientation selectivity. This is another case that highlights that orientation selectivity is not measured simply by bandwidth but also by global selectivity for preferred over orthogonal.

In a study that purports to assign a dominant role to feedforward connections in orientation, Mazet al. (2002) recorded extracellularly in V1 of awake macaques and used a reverse correlation technique very similar to the one we introduced in 1997 (Ringach et al., 1997b). However, unlike our earlier results and also unlike the results we have presented here (for instance, Figures 4–6), the results of Mazet al. were interpreted to indicate that the orientation tuning curves measured dynamically did not change shape with time. Mazet al. interpreted this as evidence supporting a feedforward scheme for orientation selectivity. We believe that the reason why their results do not agree with our results reported in Figures 4–6 is that the time sampling of their data was inadequate, and their analysis technique was insensitive to time variations in the shape of the tuning curve (for a more complete discussion, see Ringach et al., 2003).

A recent publication by Sharon and Grinvald (2002) examined the time development of orientation selectivity in cat visual cortex measured by means of optical imaging with voltage-sensitive dyes. The optical imaging signal is very nonselective at early times after a stimulus. Sharon and Grinvald did observe an increase of selectivity with time, using a global measure of selectivity, but they did not observe much change in bandwidth with time. Necessarily, the optical imaging technique averages the response properties of many neurons, so that diversity in the dynamics and in selectivity is not measurable with this technique. Nevertheless, there is a satisfyingly reasonable agreement between the optical imaging measurements and the average properties of the V1 neuron population we have measured. Both are consistent with the view that the feedforward input to V1 is very nonselective for orientation, and cortical interactions shape the orientation tuning curve.

The diversity of orientation selectivity, both in the dynamics results of Figure 6 and the steady-state results of Figures 9 and 10, is worth considering. Not all of the neurons in V1 are like the highly tuned neuron in Figure
10A. There is a need to understand what the functional consequences are for visual perception of the wide diversity of orientation tuning we have observed. Others have also reported data that indicate wide diversity of orientation tuning in cat V1 (Dragoi et al., 2000) and in ferret V1 (Chapman and Stryker, 1993) when the orientation tuning curves were analyzed with global measures of selectivity like those we have employed. As far as the mechanisms of diversity in orientation selectivity, we can offer an explanation in terms of the data in Figure 6. There, we showed that the peak orientation modulation depth $A_{\text{peak}}$ was correlated with an index of the strength of inhibition. Lower modulation depth means lower selectivity. Suppose one accepts that the feedforward input from the LGN is as broad in orientation tuning as depicted in Figure 1. Then, less inhibited cells should be less selective, and this could be one cause of diversity of selectivity. But there could also be other sources of V1 responses far from the preferred orientation that would make cells less selective. For instance, convergence of cortico-cortical excitation from many other cortical cells with different orientation preferences could broaden orientation tuning curves in V1, reducing selectivity for those cells with a lot of convergence from diverse cortico-cortical sources. It is therefore possible that there could be more than one cause of the wide diversity of orientation selectivity observed in V1.

At the end of this review, we think it is necessary to bring up the question of whether or not the intense study of orientation selectivity in V1 has enabled us to learn general principles about cerebral cortex. We would answer in the affirmative. The balance between cortico-cortical inhibition and excitation is crucial in determining the characteristics of orientation dynamics, and this should generalize to all cortical function. The speed of cortical inhibition and yet its persistence are also important to know about for future studies of cortex. Also, in studying populations of cortical cells we have been impressed with the diversity of functional selectivity in the cortex. This diversity seems like the application of a general biological principle to the cortex: don’t overspecialize. Another issue is the generalization of the visual cortex results to other cortical areas. Recent studies on the selectivity of neurons in the primary somatosensory cortex of the macaque monkey have revealed that many cells show orientation selectivity for tactile stimuli (DiCarlo and Johnson, 2000). Fits to these data indicate that excitatory and suppressive components in S1 cortex can account for tactile orientation selectivity. This suggests the testable hypothesis that similarity in architecture from one sensory cortical area to another leads to similar functional properties. Finally, the understanding of the cellular and network mechanisms has so far required the interplay between theoretical models (either analytical reduced models or large-scale simulations) to make sense of the cortical data. Going forward, we believe progress in understanding cortical function will require the continual use of theory and experiment together.

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